Storypoint Problem Exploration - titanium

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1 Storypoint Prediction: Problem Exploration

1.1 Problem Statement

In modern agile development settings, software is developed through repeated cycles (iterative) and in smaller parts at a time (incremental), allowing for adaptation to changing requirements at any point during a project's life. A project has a number of iterations (e.g. sprints in Scrum). Each iteration requires the completion of a number of user stories, which are a common way for agile teams to express user requirements.

There is thus a need to focus on estimating the effort of completing a single user story at a time rather than the entire project. In fact, it has now become a common practice for agile teams to go through each user story and estimate its "size". Story points are commonly used as a unit of measure for specifying the overall size of a user story.

1.2 Problem Formulation

Input: A string of length N that contains a story's name and description $C = \{c_1, c_2, c_3, ..., c_n\}$. For each story, a set of text embeddings that contains features $E = \{e_1, e_2, e_3, ..., e_m\}$ extracted from C has been provided.

Output: A natural number P associated with the story point of that user story

1.3 Dataset Information

Text Embeddings: Text embeddings are a way to convert words or phrases from text into a list of numbers, where each number captures a part of the text's meaning. The dataset has been preprocessed and converted into two kinds of text embeddings. You can choose to work with either of them or both: - Doc2Vec: Input strings are transformed into fixed-length vectors of size 128. These vectors capture the semantic meaning of words and their relationships within a document. - Look-upTable: Input strings are transformed into fixed-length vectors of size 2264. These vectors are obtained via transforming each word in the input strings into an identifier number, then padded to the length of the longest sample.

Dataset Structure & Format: Storypoint Estimation Dataset is stored in 3 folders labeled *raw data*, *look-up*, and *doc2vec*. Within each folder are 3 CSV files for training, testing, validation. Each csv file has the following columns: - `issuekey` : The unique identifier for a story. - `storypoint`: The correct number of storypoint. - An embedding column (`embedding` or `doc2vec`) contains text embedding vectors. The raw data csv will not have this and instead contain two columns with story `name` and `description`.

1.4 Exploration

1.4.1 Raw data exploration

[ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.feature_extraction.text import CountVectorizer
```

Output exploration

[ ]:
```
# Import raw data from the CSV file

project_name = 'titanium'

all_data = pd.concat([pd.read_csv(project_name + '/' + project_name +␣
 ↪'_dataset_train.csv'),
                      pd.read_csv(project_name + '/' + project_name +␣
 ↪'_dataset_valid.csv'),
                      pd.read_csv(project_name + '/' + project_name +␣
 ↪'_dataset_test.csv')])

print('Check the shape of the dataset', all_data.shape)
```

```
Check the shape of the dataset (2251, 5)
```

[ ]:
```
all_data.drop(['Unnamed: 0', 'issuekey'], axis=1, inplace=True)
all_data.head()
```

[ ]:
```
                                               title  \
0      android debugger running cannot back back app
1            android appversion never taken tiappxml
2         android border properties broken imageview
3   android titlebar displayed fullscreen splash s…
4                     ios drag drop map pin annotations

                                         description  storypoint
0  debug android app cant back app back hangs spl…           2
1  found bug created new release android market a…           3
2  code android border around image visible tried…           2
3  divpthere couple possibly related problems try…           2
4  divpmkannotationview support allowing map anno…           5
```

First, let take a look at the distribution of the story point:

Interpretation of Skewness Values:

- **Skewness > 0**: Right-skewed distribution.
- **Skewness < 0**: Left-skewed distribution.

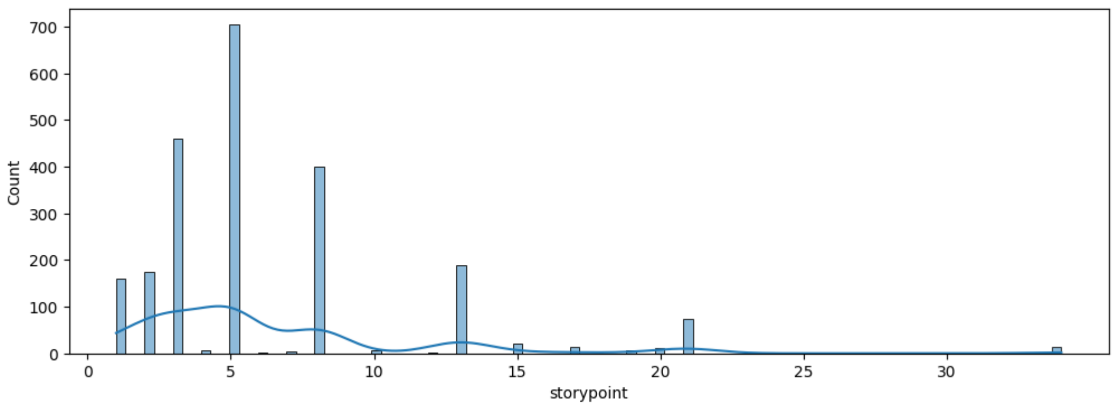
- **Skewness = 0**: Symmetrical distribution (like a normal distribution).

Interpretaion of kurtosis: - **Leptokurtic (Kurtosis > 3)**: The distribution has heavier tails and a sharper peak than the normal distribution. Data points are more likely to produce extreme values. The distribution has a higher peak and fatter tails. - **Platykurtic (Kurtosis < 3)**: The distribution has lighter tails and a flatter peak than the normal distribution. Data are fewer extreme values compared to a normal distribution. - **Mesokurtic (Kurtosis 3)**: The distribution has a similar kurtosis to the normal distribution, indicating a moderate level of outliers.

[ ]:
```
# Draw a histogram of the story points
plt.figure(figsize=(12, 4))
plt.xticks(np.arange(0, max(all_data['storypoint']) + 1, 5))
sns.histplot(all_data['storypoint'], bins=100, kde=True)

print('Skewness:', all_data['storypoint'].skew())
print('Kurtosis:', all_data['storypoint'].kurt())
```

```
Skewness: 2.18269816774033
Kurtosis: 6.414895029683273
```



[ ]:
```
tmp = pd.concat([all_data['storypoint'].value_counts(),
                 all_data['storypoint'].value_counts() / all_data.shape[0] *␣
 ↪100],
                axis=1, keys=['Counts', 'Percentage (%)'])
tmp.head(20)
```

[ ]:

storypoint	Counts	Percentage (%)
5	704	31.274989
3	459	20.390937
8	400	17.769880
13	189	8.396268
2	175	7.774323
1	160	7.107952

21	73	3.243003
15	20	0.888494
17	14	0.621946
34	14	0.621946
20	12	0.533096
4	7	0.310973
10	6	0.266548
19	6	0.266548
7	5	0.222124
30	2	0.088849
12	2	0.088849
6	2	0.088849
33	1	0.044425

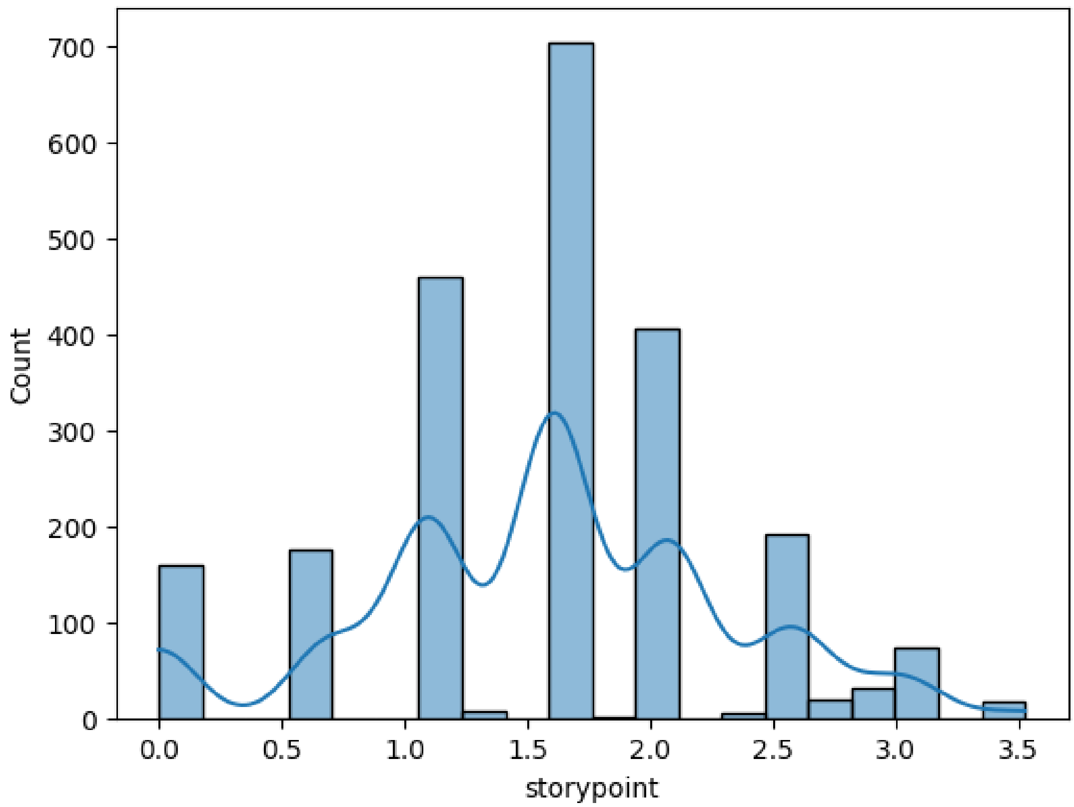
At the first sight, this data is bad. Then take a look at the statistic values, this data is even worse. Its distribution of the label is **right-skewed** and **leptokurtis**. This means if we use this to train model, the right side of the data can be the outliers and make the models become unsuable.

I will try 2 solutions: - Use log-scale on the label - Remove all the examples with label greater than a threshold (20, 30 or 40)

The first solution: logarithm magic

[ ]:
```
sns.histplot(np.log(all_data['storypoint']), bins=20, kde=True)
```

[ ]: <Axes: xlabel='storypoint', ylabel='Count'>

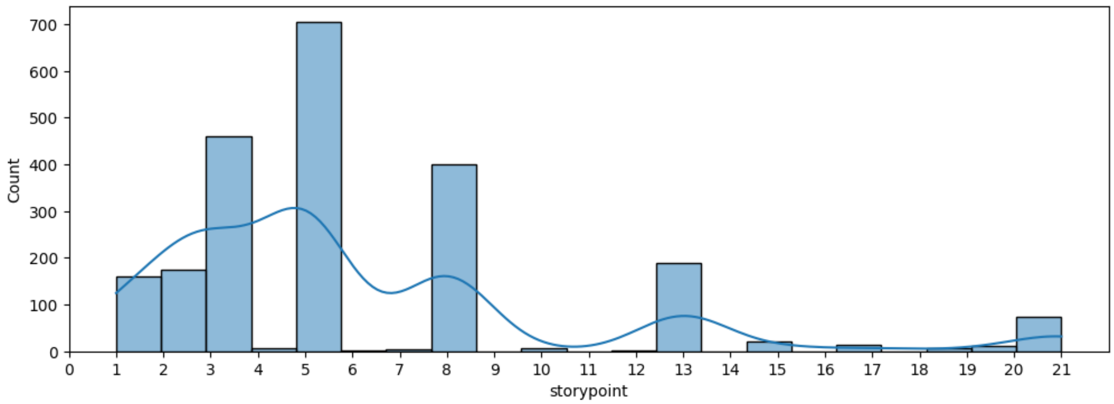


The second solution: Dismantle and Cleave

```
[ ]: threshold = 21 # This threshold means that we will take all the examples with␣
      ↪story points less than or equal to 21

     new_data = all_data[all_data['storypoint'] <= threshold]
     plt.figure(figsize=(12, 4))
     plt.xticks(np.arange(0, max(new_data['storypoint']) + 1, 1))
     sns.histplot(new_data['storypoint'], bins=threshold, kde=True)
     print('Fitered percentage: ', round(1 - new_data.shape[0] / all_data.shape[0],␣
      ↪2) * 100, '%')
```

```
Fitered percentage:  1.0 %
```



Input exploration The input of this problem is 2 texts: title and description. First we will find some statistics:

```
[ ]: title_lengths = all_data['title'].apply(lambda x: len(x.split(' ')))
print('Title analysis:')
print('   - Mean length:', round(title_lengths.mean()))
print('   - Min length:', title_lengths.min())
print('   - Max length:', title_lengths.max())

description_lengths = all_data['description'].apply(lambda x: len(x.split(' '))␣
 ↪if type(x) != float else 0)
print('Description analysis:')
print('   - Mean length:', round(description_lengths.mean()))
print('   - Min length:', description_lengths.min())
print('   - Max length:', description_lengths.max())
```

```
Title analysis:
   - Mean length: 6
   - Min length: 2
   - Max length: 17
Description analysis:
   - Mean length: 68
   - Min length: 0
   - Max length: 1517
```

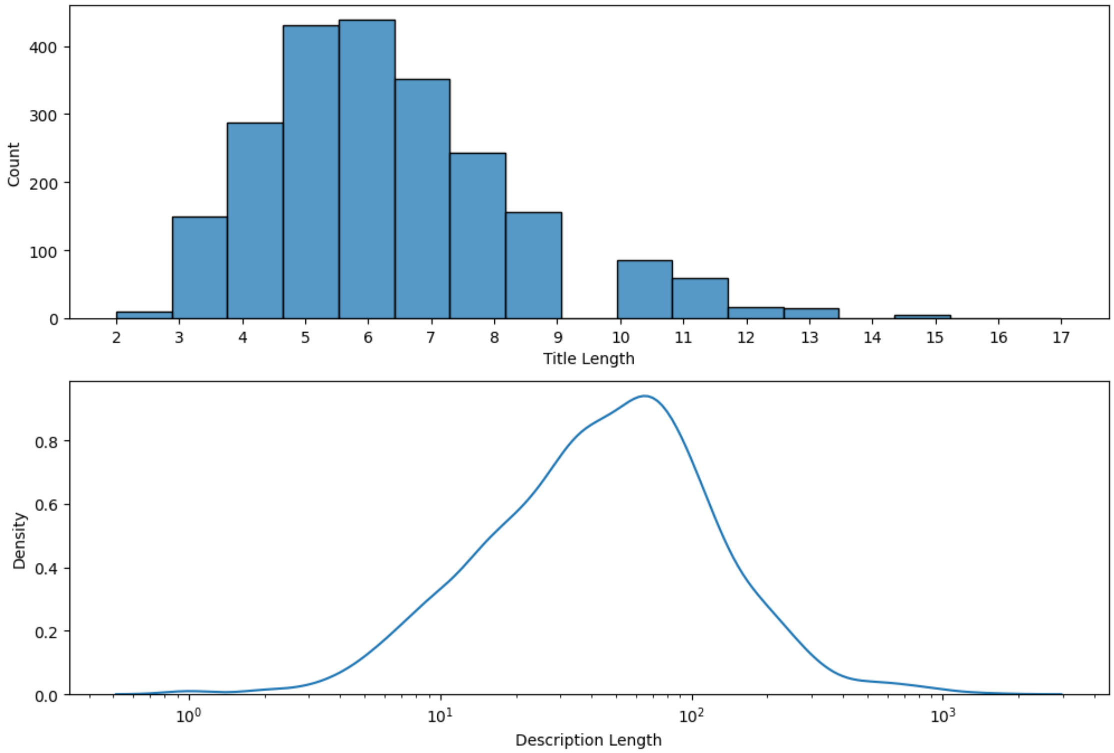
Plot the histogram of the title length and KDE of the description length (exclude 0):

```
[ ]: plt.figure(figsize=(12, 8))

plt.subplot(2, 1, 1)
plt.xticks(np.arange(0, max(title_lengths) + 1, 1))
plt.xlabel('Title Length')
sns.histplot(title_lengths, bins=max(title_lengths))
```

```
plt.subplot(2, 1, 2)
plt.xlabel('Description Length')
plt.xscale('log')
sns.kdeplot(description_lengths[description_lengths > 0])
```

[ ]: <Axes: xlabel='Description Length', ylabel='Density'>



I think we should check the correlation between title length and description length:

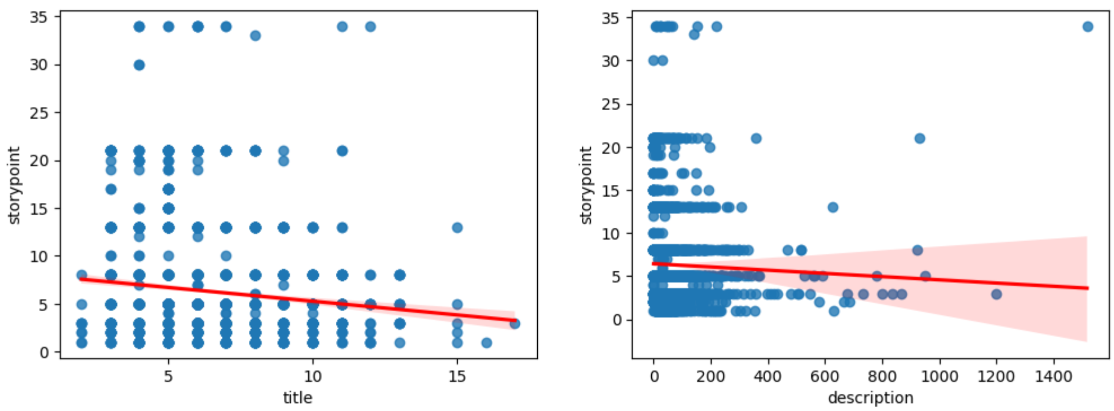
[ ]:
```
plt.figure(figsize=(12, 4))

plt.subplot(1, 2, 1)
plt.xticks(np.arange(0, max(all_data['title'].apply(lambda x: len(x.split('␣
↪')))) + 1, 5))
sns.regplot(x=all_data['title'].apply(lambda x : len(x.split(' '))),
            y=all_data['storypoint'],
            line_kws={'color': 'red'})

plt.subplot(1, 2, 2)
sns.regplot(x=all_data['description'].apply(lambda x : len(x.split(' ')) if␣
↪type(x) != float else 0),
            y=all_data['storypoint'],
```

```
line_kws={'color': 'red'})
```

[ ]: <Axes: xlabel='description', ylabel='storypoint'>



Yep! At first, I think we can find the relation like "longer length = more storypoint" but this is not like that.

Let dive deeper in the input:

Title analysis:

[ ]:
```
count_vectorizer = CountVectorizer()
count_vectorizer.fit(all_data['title'])

dictionary = pd.DataFrame(list(count_vectorizer.vocabulary_.items()),␣
↪columns=['word', 'frequency'])
dictionary.sort_values(by='frequency', ascending=False, inplace=True)
print(dictionary.shape)
dictionary.head(10)
```

```
(3036, 2)
```

[ ]:

	word	frequency
2946	zooming	3035
1476	zoom	3034
2673	zip	3033
869	zindex	3032
600	youtubeinapp	3031
1429	yosemite	3030
1632	yields	3029
2348	yellow	3028
1923	year	3027
1958	yaml	3026

Description analysis:

[ ]:
```
count_vectorizer = CountVectorizer()
count_vectorizer.fit(all_data[all_data['description'].isnull() ==␣
 ↪False]['description'])

dictionary = pd.DataFrame(list(count_vectorizer.vocabulary_.items()),␣
 ↪columns=['word', 'frequency'])
dictionary.sort_values(by='frequency', ascending=False, inplace=True)
print(dictionary.shape)
dictionary.head(20)
```

```
(18923, 2)
```

[ ]:

	word	frequency
5815	zznumofanswersz	18922
17825	zusersjorgenbuderlibraryapplication	18921
17808	zusersjorgenbuderdocumentsappceleratorstudiowo…	18920
17805	zusersjorgenbuderdocumentsappceleratorstudiowo…	18919
17819	zusersjorgenbuderdocumentsappceleratorstudiowo…	18918
16174	zorder	18917
18367	zoomviewaddtiuicreateimageview	18916
18362	zoomview	18915
18363	zoomscale	18914
7386	zooming	18913
8417	zoomed	18912
4357	zoom	18911
6855	zncatransactionobservercallbackepcfrunloopobse…	18910
6854	zncatransactioncommitev	18909
10417	zncalayerrunanimationcallbacksepv	18908
6848	zncalayerlayoutifneededepnstransactione	18907
6850	zncalayerlayoutanddisplayifneededepnstransactione	18906
6852	zncacontextcommittransactionepnstransactione	18905
7693	znartabortstatedumpthreadernstbasicostreamicns…	18904
7694	znartabortstatedumpernstbasicostreamicnschartr…	18903

Yet I don't find any thing special about the words in input except so many things are bad.

1.4.2 Solving strategies

My first intuitation in this problem is that the hard part is not on the algorithm we use, it is on the **embedding** part. Therefore, in case the given embedded datasets work not properly, I will use a better embedding method which is **Bidirectional Encoder Representations from Transformers (BERT)**. Also, I will try an old way to embedding the text too: **Bag of words**.

In conclusion, I will have 4 ways to embed the text: - doc2vec (already available) - Look up (already available) - Bag Of Words - BERT

About algorithm, I will try all the regression algorithm that may give a good result:

- Ridge Regressor
- Support Vector Regressor

- Random Forest Regressor
- Gradient Boosting
- XGBoost
- Lightgbm
- Blended

Maybe, we can change the problem to the classification problem with 100 labels (desparation confirmed). In the classification problem, I will use: - Support Vector Classifier - Softmax Regression (Multinomial Logistic Regression) - Random Forest - Adaboost - XGBoost

Thanks to the libaries, the implementation of all the algorithm shrinks to its minimum form.

At last, there is still a situation that all of mentioned model don't give a good result. This gamble is thrilling (hopeless).

"But would you lose?"

Nah, I'd win.